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Using data from connected thermostats to track large power outages in the United States

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Abstract

The detection of power outages is an essential activity for electric utilities. A large, national dataset of Internet-connected thermostats was used to explore and illustrate the ability of Internet-connected devices to geospatially track outages caused by hurricanes and other major weather events. The method was applied to nine major outage events, including hurricanes and windstorms. In one event, Hurricane Irma, a network of about 1,000 thermostats provided quantitatively similar results to detailed utility data with respect to the number of homes without power and identification of the most severely affected regions. The method generated regionally uniform outage data that would give emergency authorities additional visibility into the scope and magnitude of outages. The network of thermostat-sensors also made it possible to calculate a higher resolution version of outage duration (or SAIDI) at a level of customer-level visibility that was not previously available.

1. Introduction

Even brief interruptions in the supply of electric power to consumers can lead to significant economic and human costs [1]. For this reason utilities devote considerable resources to rapid detection and assessment of power outages. This situation is especially true in developed countries; for example, customers in most European countries experienced fewer than two hours without power in 2016 [2].

Electricity outages cost U.S. consumers roughly $44 billion in 2015 [3]. In spite of continuing efforts to improve the grid, the frequency and duration of power outages has not appreciably fallen in the last two decades and may have in fact risen [4], [5], [3]. Steps are being taken to improve the reliability of the grid at points of generation, transmission, and distribution [6]. However, after an outage occurs, the key to minimizing economic consequences of an outage is to quickly become aware of its presence and scope. This information enables the utility and other emergency authorities to most efficiently mobilize resources to restore services [7].

Real-time outage detection remains an essential activity for electric utilities. Most utilities employ an outage management system (OMS) to deal with these events [8]. The OMS draws information from supervisory control and data acquisition (SCADA) devices, customer telephone calls, smart meters, social media, and other sources [9]. About half of U.S. residential customers are connected to smart meters (or advanced metering infrastructure—AMI). Modern smart meters detect outages and transmit a “last gasp” signal at the time of the outage, which is especially valuable in alerting the OMS of an outage and providing a location. However, the transmission of the last gasp signal is not assured. These signals will not reach the OMS, or may be delayed, if the mesh network is compromised [10].

Often the challenge for an OMS is not to obtain data but to avoid congestion from superfluous or duplicate data [11]. Local gatekeepers are often established to reduce duplicate notifications, combine messages, or verify outages through pinging. Utilities still rely heavily on customer calls to detect outages. One survey of utilities in 2015 [12] claimed that customer calls were still the primary source of outage notifications, far higher than SCADA or smart meters. Only 16 percent of utilities used their smart meters as the primary source of power failure alerts on “blue-sky” days and 12 percent during storms. Handling excessive customer calls is an expensive problem, too. For example, 30 percent of customers call more than once during an outage because they do not know when their power will be restored [13].

Various services have emerged to aggregate the OMS data and present a national picture of outages, often in near real time. One service [14] compiles OMS data from over 600 U.S. utilities and offers outage information to customers at many different levels of geographical and historical resolution. The quality of this information is, of course, only as good as the OMS data supplied to it.

The drawbacks and weaknesses of current outage detection systems have stimulated the development of new techniques to identify outages. These approaches are notable for their diversity, including satellite imagery, mobile telephones, social media, and status of Internet connections. Curiously, most of these experiments have taken place outside of the traditional utility environment. These explorations are briefly described below.

Satellite imagery has been proposed as means to identify large outages [15] and used to show the impact of power outages caused by Hurricane Sandy. Similar assessments were undertaken after the Fukushima nuclear disaster [16]. The approach involves comparison of satellite images of the affected area to baseline photographs. The drawbacks of this approach are low resolution, delay (until night), and susceptibility to cloud cover.

Mobile telephones have been used as outage sensors [17]. This approach relies on the fact that a smartphone can detect a power outage based on its own power state. A smartphone will change its state when plugged into a charger. If power is interrupted then the smartphone will detect a change in state. It can further distinguish between a benign unplugging and a power outage through filters and other inputs. After downloading a special app, the telephone can notify a central entity of an outage. The system was tested in Kenya.

Sun et al. [18] and Hultquist et al. [19] tracked social media—Twitter—and, through semantic analysis of content, identified messages related to power outages. This methodology enabled the outages to be identified and geographically located.

Most devices connected to the Internet rely on grid-supplied power because the data flows through a Wi-Fi router and a modem. When an outage occurs, the devices lose their network connection and will go “dark,” that is, the service provider no longer receives data. Thus, loss of a network connection can serve as an implicit outage sensor. Shulman [20] proposed a means of identifying network/power outages during periods of intense storms. The method determines connectivity by pinging a representative sample of residential IP addresses in the region affected by the storm. When the pings were not returned (and after various error filters were applied), the connection was assumed to be down. This procedure could determine the extent of failed connections but could not distinguish between network and power outages. Heidemann et al. [21] employed a similar approach to investigate the frequency and scope of Internet outages. He found that a significant fraction of Internet outages in his dataset could be attributed to power outages, notably those related to Hurricane Sandy.

The “industrial Internet of Things” (IIoT) was used by Simoes et al. [22] to track power outages in Portugal. Many commercial operations have networks connecting hundreds—or even thousands—of geo-located devices, including automated cash dispensers, mobile telephone towers, and building security systems. These devices are regularly polled, so when they fail to respond, a power outage can be inferred. The electric utility created an open, Internet-based communication channel, for customers to send outage events. A specially designed program then transforms the submissions into a structure that can provide situational awareness to the grid operator.

The research summarized above demonstrated that a range of networks can track power outages. At the same time, it has been demonstrated that failures in the power grid lead to interruptions in the Internet. In this paper we explore the ability of Internet-connected devices to act as a highly distributed network of electricity grid sensors and to provide meaningful information to grid operators, emergency authorities, and policymakers.

2. The Connected Thermostat Dataset

The network of Internet-connected thermostats (CTs) offers many of the same features as the IIoT described above. These thermostats transmit data via the Internet to a service provider as frequently as every five minutes. When a thermostat goes dark, the most likely cause is a power outage. The thermostats are tracked in a consistent manner, spanning utility service areas, states, and regions. This broad coverage is important in the United States because many outages involve multiple utilities and grid operators. In the United States, there are at least six million installed CTs, and the population is growing at a rate of about 20 percent per year.

Thermostat data were obtained through the ecobee Donate Your Data (DYD) program [23]. Ecobee sells and manages CTs primarily in North America. The DYD program enables users to anonymously donate their operation data for research use. User data are gathered in servers managed by ecobee. Every fifteen minutes, the ecobee thermostat records the thermostat setpoints, the actual inside temperature, relative humidity, and HVAC runtime. Some models record occupancy and temperatures in other rooms. These data are collected by the thermostat and then transmitted via Wi-Fi and the Internet to an ecobee server.

Ecobee shares limited metadata about each participating DYD home with researchers, including the home's location (city and state or province), its approximate floor area, and age. Ecobee also shares outside temperatures from nearby weather stations. Weather information was not used in this analysis but may be useful for future outage-related research.

The DYD program began in 2015, and the number of participants increased rapidly. Figure 1 shows the monthly trend of the number of participants (and devices) in this study. By late 2018, about 60,000 homes participated in the DYD program. This data collection program is orders of magnitude more detailed than anything before it. For example, the Residential Energy Consumption Survey (RECS) [24] is the only national program collecting similar data. RECS surveys about 5,600 homes once every four years. The survey relies on consumer responses for thermostat settings, and monthly utility bills are obtained from the local utility. The DYD dataset can provide extraordinary insights into heating and cooling behaviors in North American homes. For example, Huchuk et al. [25] used data from over 10,000 DYD thermostats to investigate how different climates, seasons, and utility tariffs affected the occupants' selection of indoor temperatures.

The DYD data used in this study begin in January 2015 and end in September 2017. The number of participating homes climbed during this period from 1,000 to 20,000. Figure 1 shows the rising number of thermostats during the study period. The numbers in the ten largest states are broken out. Note that about half of the thermostats are located in the remaining states. The DYD homes appear to be representative of the national building stock. We verified that the homes in the DYD homes closely resembled the subset of single-family homes in the RECS dataset by comparing home size and number of occupants [26].

Each DYD participant reported the city in which the thermostat was located. The city was then mapped into its respective county. This level of geospatial precision appeared reasonable. A county-level resolution also facilitated later comparison with other data sources, such as census and utility service maps. Note that ecobee could apply greater geospatial precision in the future but it limited location data in the DYD dataset to cities so as to preserve customer confidentiality.

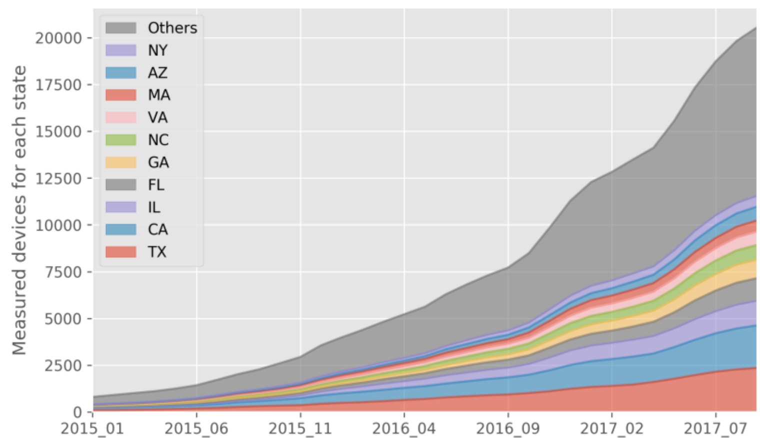


Figure 1. Monthly trend of participating thermostats by state

The files were cleaned to eliminate a range of defects, such as discontinuities caused by daylight savings time and missing data. Some missing data also resulted from the procedures ecobee used to anonymize the DYD participants and transfer files to researchers. The gaps appeared in a mostly random manner. The lost data represented less than 5 percent of the overall dataset; however, the resulting gaps were difficult to distinguish from power or network outages. (Missing data rates have declined below 1 percent in more recent data transfers.)

3. Tracking Power Outages Caused by Hurricane Irma

Hurricane Irma struck the Southeastern United States on September 8–24, 2017 and caused many deaths, injuries, and extensive economic damage. The continental path of Hurricane Irma is shown in Figure 2. The hurricane passed through at least four states, which were serviced by four large electric utilities and many smaller utilities [27].

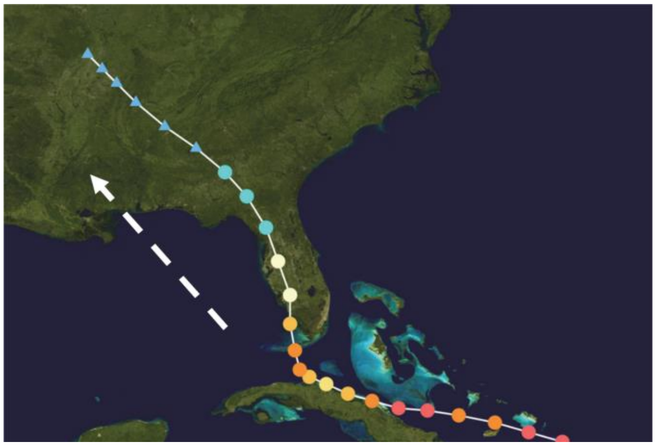


Figure 2. Path of Hurricane Irma (September 8–24, 2017). Each dot corresponds to one day. The color indicates Irma's severity.

The geospatial impact of Hurricane Irma is revealed in the maximum fraction of inactive thermostats observed in each county in Figure 3. White areas represent counties with fewer than 30 thermostats. (These are typically counties with fewer people.) The most seriously affected counties were in southwest Florida, but high outage fractions also occurred in counties as far north as central Georgia, reflecting severe local conditions or less storm-resistant electricity networks. This figure captures the scale and complexity of Irma's impact in four states and in the service areas of many different utilities.

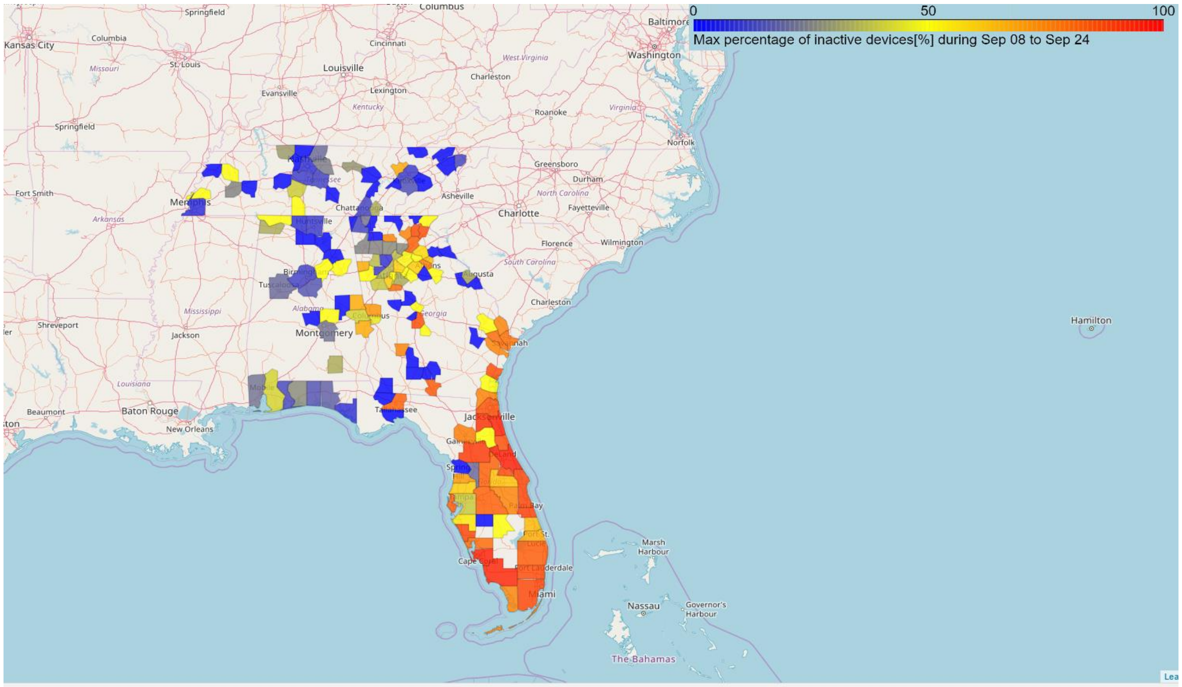


Figure 3. Maximum fractions of inactive thermostats for each county (September 8–24, 2017)

The number of affected customers in each county was extrapolated from the fraction of dark thermostats in each county and the number of homes in that county. For example, if 20 percent of thermostats were dark and the county had one hundred thousand homes, then 20,000 customers were estimated to be without power. The number of customers without power at 15-minute intervals is shown in Figure 4. Using this method of extrapolation, over five million homes were without power at the peak on September 11. Figure 4 also shows that restoration of power took many days and that over two million customers still lacked power five days after the hurricane hit.

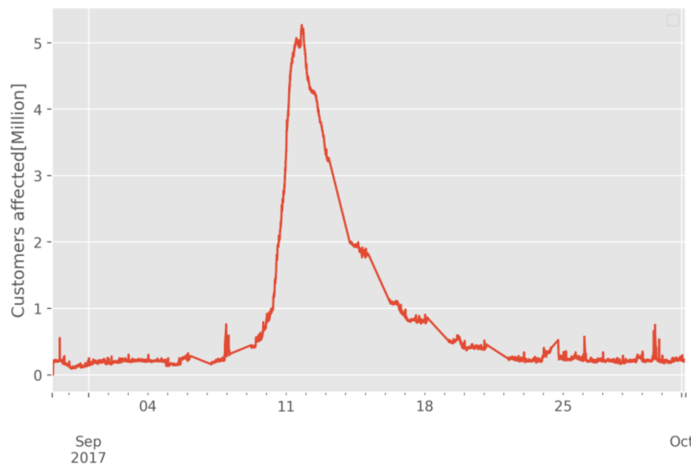


Figure 4. Customers affected by Hurricane Irma in the four most affected states

Each county was affected differently by Hurricane Irma, both in severity and timing. Figure 5 shows the time sequence of thermostat outages by county. (Counties with fewer than 30 thermostats were not plotted.) The counties are stacked by increasing latitude. Since Hurricane Irma traveled south to north, the lag in outages caused a small but distinct time shift in each county's peak. In addition, the magnitude of the peak and total impact diminished as Irma moved north.

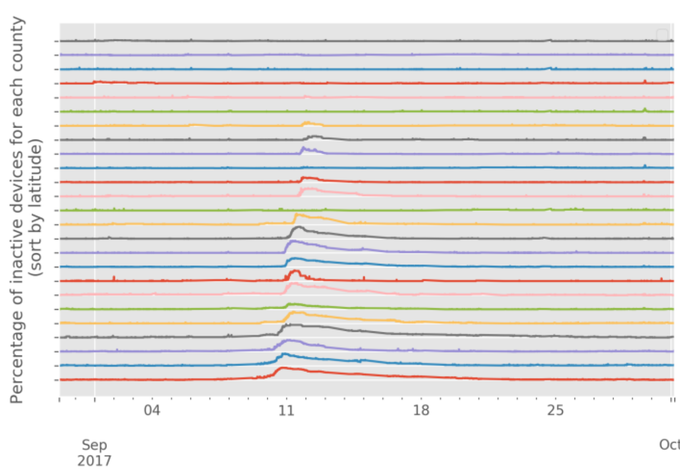


Figure 5. Transition of power outage rates for each county with more than 30 thermostats

4. A Power Outage Caused by a Wind Storm

A severe wind storm struck the middle west United States on March 8, 2017, which led to widespread power outages in Michigan and neighboring states [28]. The storm was much less severe than Hurricane Irma, and the region has a sparser network of DYD thermostats compared to Florida; nevertheless, the outage is still clearly displayed and its geospatial impact can be inferred. Figure 6 shows the maximum fraction of inactive thermostats in each county during the event. Only counties with more than 30 DYD homes are displayed. The extent of the storm is evident, from Wisconsin to central Indiana and Ohio. At least two different grid operators participate in the control of the affected region, and more than five electric utilities serve this area, each with its own outage management system. A unified sensing network, with consistent outage metrics, was not possible until the Internet-connected thermostats became available.

Figure 7 shows the progression of outages over time. It displays the fraction of off-line thermostats for the six counties with the largest number of DYD homes. They are stacked from south to north (similar to that in Figure 3 for Hurricane Irma). Newspaper reports suggest that the storm traveled from northwest to southeast, but this is not evident from the DYD data, possibly because it traveled so rapidly. On the other hand, the orientation of the storm, that is, northwest to southeast, is clear.

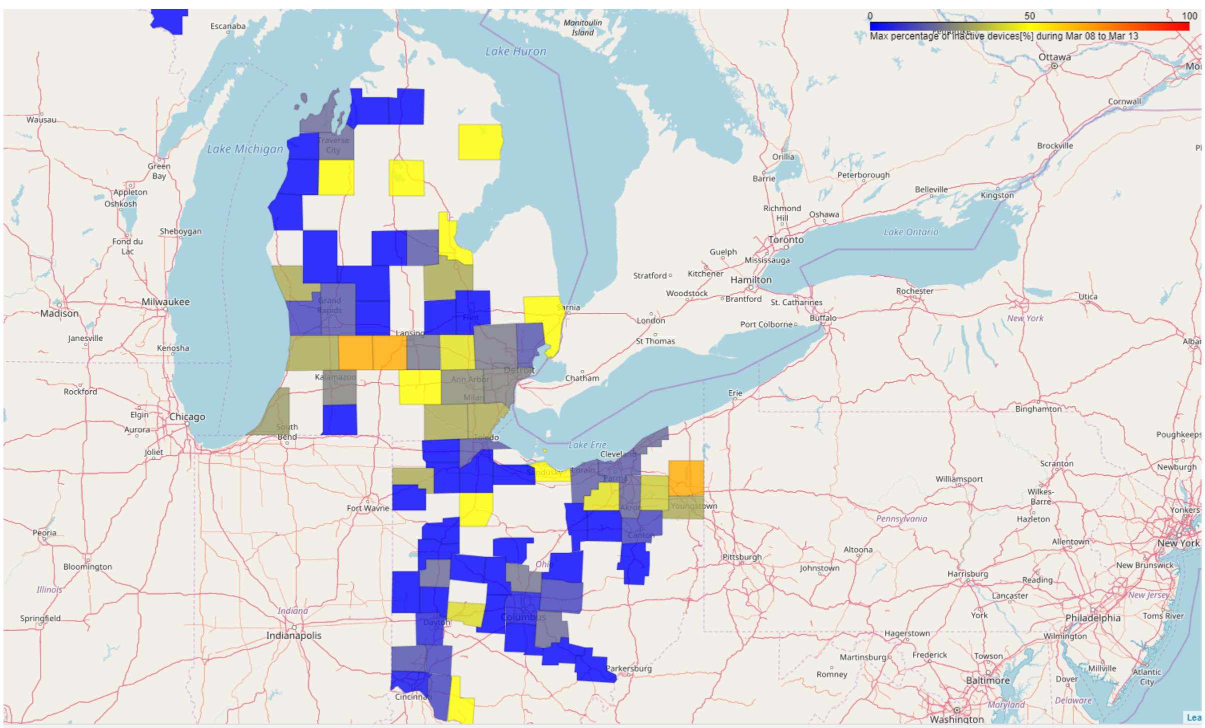


Figure 6. Maximum power outage rates for each county (March 8–13, 2017)

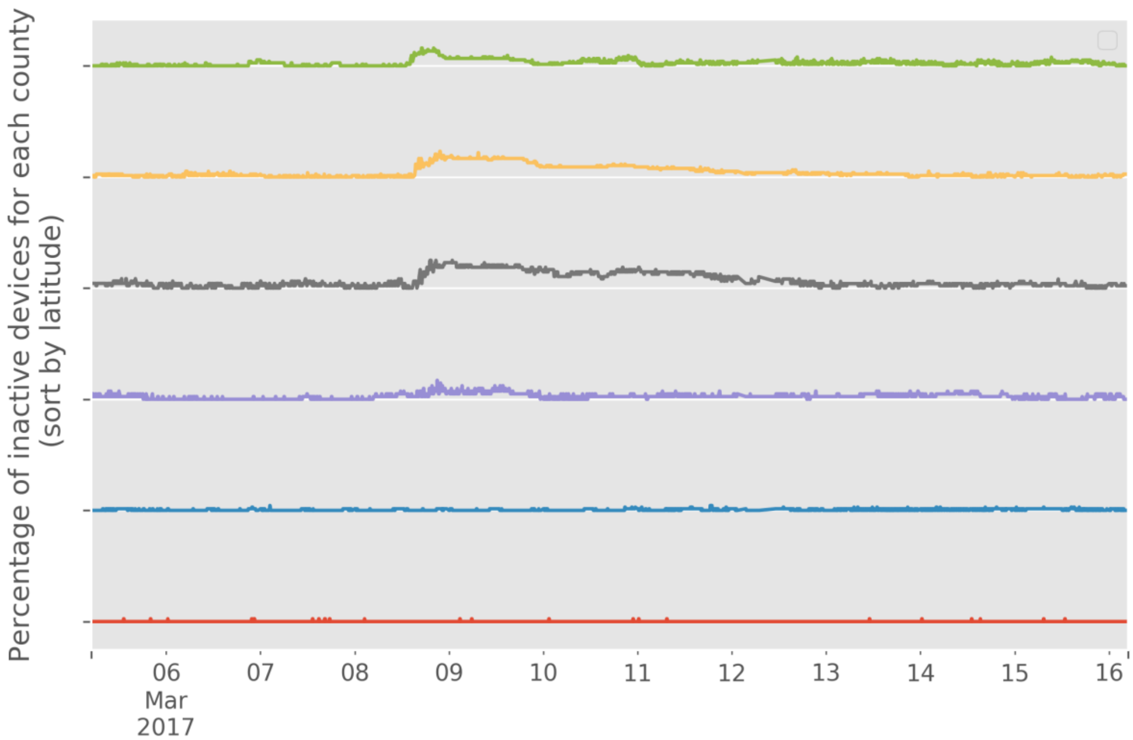


Figure 7. Transitions of power outage rates for each county

5. Power Outage Metrics from Connected Thermostat Data

The CT data also makes it possible to calculate standardized metrics related to outages. The number of customer outage-hours was estimated for each county affected by Hurricane Irma. This is analogous to the System Average Interruption Duration Index (SAIDI), except that CT data can provide higher spatial and temporal resolution than is normally available from SCADA data and other sources. Results are shown geospatially in Figure 8 and sorted by declining values in Figure 9. With this higher resolution, it becomes possible to more clearly distinguish between areas where many customers experienced brief outages and areas where a few customers experienced long outages. (The SAIDI metrics would be the same, but the type of disruption will be different.) For example, higher outage-hours per customer will lead to more food spoilage in refrigerators or health impacts among vulnerable populations. Therefore, high-resolution identification of outage-hours can be an important indicator of disproportionate economic damage caused by power outages in specific neighborhoods, communities, or counties. The figures show that, while southwestern Florida experienced the highest outage rates, southeastern Florida experienced the greatest number of customer outage-hours.
The higher outage-hours mostly reflects the greater population in southeastern Florida (principally, Miami).

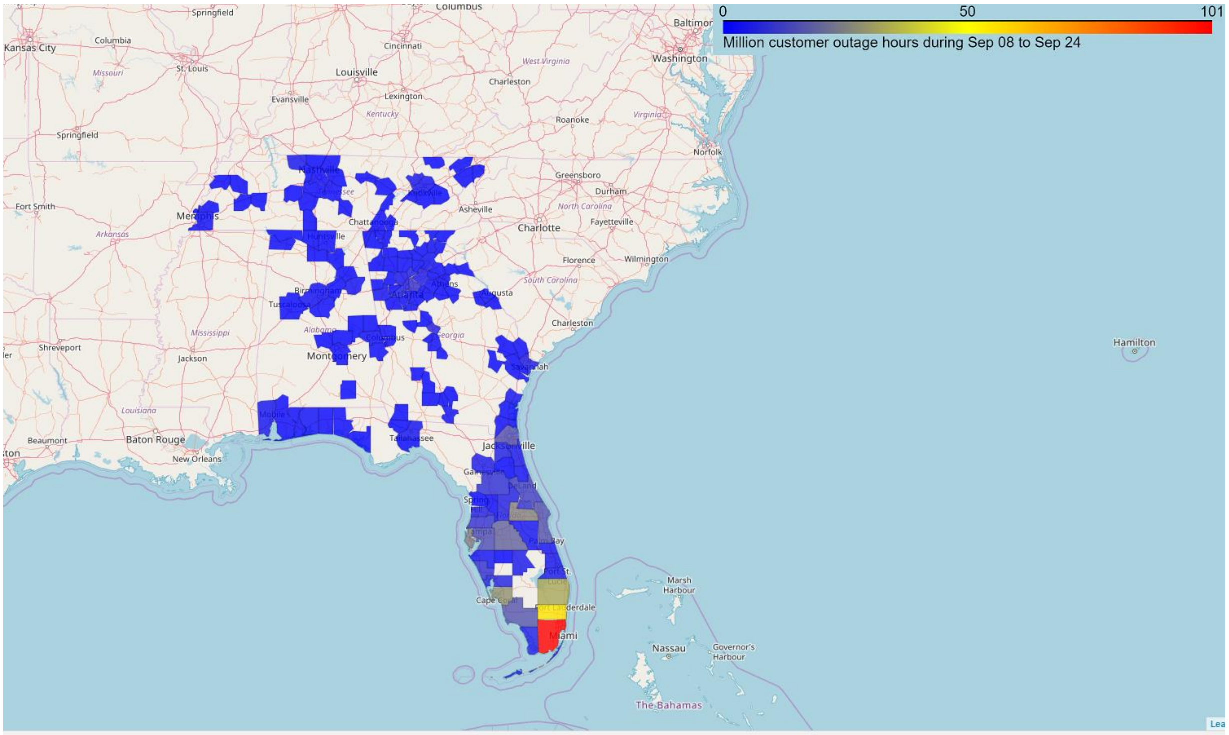


Figure 8. Maximum customer outage-hours for each county (September 8–24, 2017)

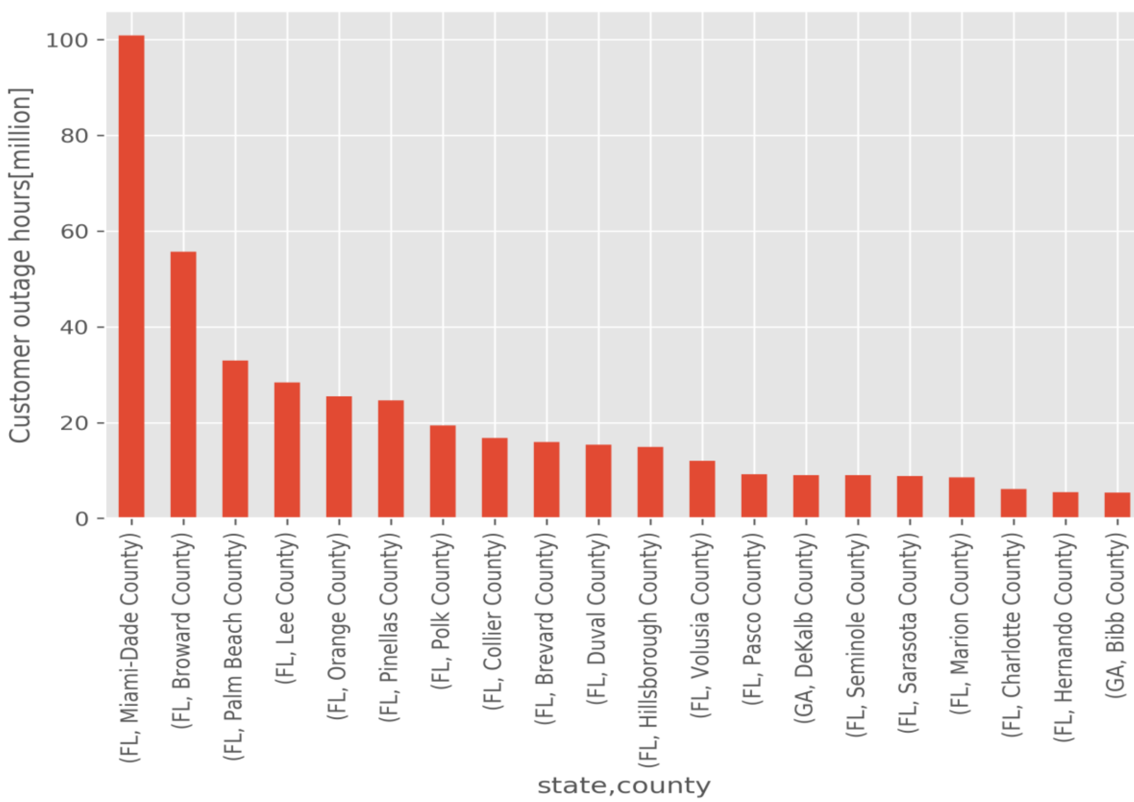
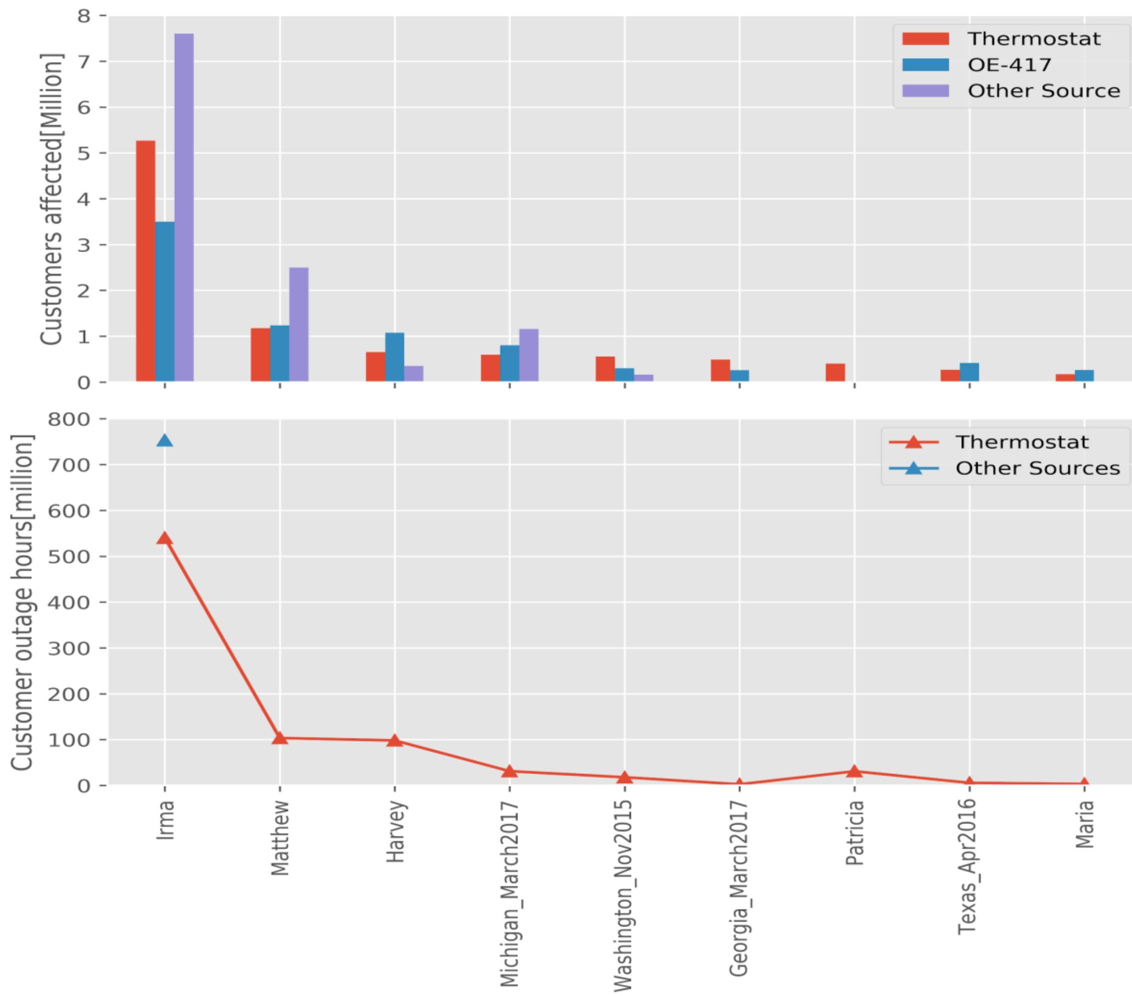


Figure 9. Customer outage-hours for each county by Hurricane Irma

Utilities are required to submit Form OE-417 when a significant outage occurs [29]. The U.S. Energy Information Administration (EIA) lists 12 criteria that require a utility to report an outage, one of which is loss of service to 50,000 or more customers for one hour or more. These reports are displayed in Figure 10a. In some cases other sources estimated the number of affected customers, and they are also shown in Figures 10a and 10b. These estimates were diverse, inconsistent, and often made prior to a retrospective evaluation. For example, many utilities estimated affected customers during the outage itself and did not submit updates. The techniques described for Hurricane Irma and the Michigan wind storm were applied to nine major power outages. The number of consumers affected and total consumer outage-hours were estimated (see Figures 10a and 10b). These values were compared to utility submissions to the EIA for the same events.



Figures 10a and 10b. Comparison of customers affected and customer outage-hours for selected major power outages (2015–2017)

The three sources of outage information tracked closely with respect to ranking but differed with respect to magnitudes of affected customers and outage-hours. Hurricane Irma was the largest outage, regardless of metric and source of information.

6. Discussion

6.1 Using Internet-Connected Devices as Power Outage Sensors

We demonstrated the capability of a network of Internet-connected, geo-located devices to track power outages. The approach reveals the geo-spatial impacts, chronology, and intensity of an outage. It provides a regional outage perspective based on a consistent sensor network and methodology.

We also demonstrated how the thermostat data can be converted into granular metrics suitable for emergency management and policy analysis. The first metric is the number of customers that lost power during an event. This number is often uncertain, especially when the outage covers more than one utility or grid operator. The number of affected customers can also be shown as a time-trajectory or geo-spatially. This information can help recovery efforts target the most severely affected areas. A SAIDI with much higher geospatial resolution pinpoints the overall intensity of the outage event. The intensity of Hurricane Irma, for example, becomes more evident when comparing its outage-hours to those of Hurricane Matthew. A geo-spatial breakdown of customer outage-hours by county can assist emergency authorities in locating the most severely impacted areas. Insurance companies would find such data useful when evaluating claims.

6.2 Uncertainty of a Grid Sensor Network Comprised of Internet-Connected Devices

New types of uncertainties arise with this method of estimating outages. These uncertainties fall into two categories: (1) reliability of the network disconnection as a proxy for an outage sensor, and (2) validity of extrapolations from the population of DYD homes to the general population. Some of the uncertainties are described below.

The underlying assumption behind our approach is that, when the service provider no longer receives information from a thermostat, a power outage has occurred. But there are other explanations for a thermostat going dark that do not involve a power outage. Possible explanations include the following:

- *The Internet network fails.* Data networks have more interruptions than power networks, [30] but these interruptions are typically brief and other features are present to mitigate their impact [31]. Large network failures can be identified and filtered out.

- *The occupant switches off the thermostat*. This happens sometimes during periods of mild weather when no heating or cooling is required.
- *The occupant unplugs or switches off the modem.* This happens rarely and briefly, such as when the occupant moves the modem.

These types of network interruptions will occur at a low, continuous level in mostly random ways. We therefore conclude network interruptions not caused by power outages introduce a low-level “noise” to the DYD or other thermostat data. These false signals will overstate the frequency of outages. This uncertainty is small but needs to be quantified through further research and algorithms developed to minimize these effects [31].

The number of affected customers relies on an extrapolation from a small number of homes with connected thermostats. Since the highest level of geo-spatial resolution is the county, power outages affecting only a fraction of a county will give ambiguous results. In Florida, the extrapolation is based on only 1,204 DYD thermostats (less than 0.02 percent of Florida’s homes). Reliance on such a small sample introduces uncertainty into the county, state, and regional outage estimates, especially if the DYD homes differ from the rest of the population.

We checked to determine if DYD homes were significantly different from the national stock of single-family homes by comparing the findings from the most recent Residential Energy Consumption Survey [24] to the DYD homes. The RECS (single-family) and DYD homes were similar in floor area, age, and number of occupants. We concluded that the DYD homes were similar enough to the national stock to not cause significant distortions.

Other differences might arise at the county level. For example, some counties may have higher fractions of apartments, few of which are in the DYD dataset (so far). The extrapolation may also be misleading in counties with a large fraction of electricity consumed by industrial or commercial sectors. The problem will probably become less important after aggregation; still, further research would be useful.

The accuracy of this sensor network has not been compared with ground truth. A verification would require finding a region meeting many criteria, including the following:

- A cooperating utility whose residential customers are equipped with smart meters that store and transmit outage information
- A high concentration of homes with CTs
- Several power outages during the study period
- Customer permissions to release both utility and CT data

These criteria are logistically challenging. Moreover, smart meters have their own reporting shortcomings, so they may be an imperfect ground truth. Nevertheless, two reality checks were performed to verify the accuracy of our approach.

In the first verification, the number of customers suffering outages during Hurricane Irma were compared using DYD data and detailed estimates from the Florida Public Service Commission.

The Florida Public Service Commission estimated the number of affected customers by tabulating the number of customers known to be on each failed subsystem and feeder line having SCADA. Some smaller utilities are not included. This approach offers a means to estimate outage impacts at a highly granular level (but does not rely on smart meters). Both methods registered peak outages within a few hours of each other. The utilities reported slightly more customers without power at the peak than were extrapolated from DYD data: 6.2 million versus 5.6 million customers—that is, a difference of roughly 10 percent.

A second comparison was made between the total number of customer outage-hours from the five largest events in 2017 (see Figure 10b) to an estimate of national outage-hours based on EIA data. Table 1 summarizes the results.

Table 1. Outage comparison for major and ordinary events in 2017

	EIA	**DYD**
Definition of major event	Utility Reports from Form OE-417 Filings	Outages Revealed by Inspection of DYD Data
Customer outage-hours caused by major events (millions)	786	645
Customer outage-hours caused by ordinary events (millions)	262	N.A.

Table 1 shows that the utilities reported 786 million outage-hours to the EIA in 2017. This compares to 645 million outage-hours revealed by inspection of the DYD data. Thus, the DYD data captured roughly 82 percent of the reported major outages. While not equal, this comparison shows that the two very different approaches yield roughly similar results. Equality should not be expected because some utilities did not report their outages. On the other hand, the DYD outage-hours included all utilities but are based on only the five largest outages investigated in this study. With further improvements in data processing, connected devices could be an accurate means of estimating outage-hours from major outage events.

Comparisons of ordinary outage events are impossible with current techniques. The DYD data contain too much “noise”—missing data, network outages, etc.—to observe power outages that occur in small regions and at very low frequencies. Future improvements in algorithms should be able to better distinguish actual power outages from other reasons that the connected device is not transmitting data, but the noise can never be completely eliminated.

6.3 National Grid Reliability Metrics Using Internet-Connected Devices

Utilities and governments have invested more than 32.5 billion dollars between 2008 and 2017 on improvements to the grid and expect to invest much more [32]. A comprehensive and consistent set of metrics is needed to gauge the success of these and future investments, some of which must address power outages. The EIA compiles utility reports of key outage metrics related to frequency and duration of outages, the System Average Interruption Frequency Index (SAIFI), and SAIDI. Only 30 percent of the utilities typically file reports, but these are the largest and therefore represent a much larger fraction of total customers. Each utility employs slightly different procedures and assumptions in its calculation, though utilities serving more than 50 percent of U.S. customers claim to follow the IEEE standard 1366 [3], [33]. Our method of measuring outages with Internet-connected devices makes possible a simple, consistent procedure to collect national outage data.

The network's geospatial resolution and accuracy depends on the number and distribution of its sensors. Table 2 lists our estimates of the populations of various geospatially linked, networked devices that could serve as grid sensors. An important feature of these networks is the number of units linked to a single, national entity. A single entity simplifies collection and processing of consistent, national, metrics. Consumer privacy also can be more easily maintained when a single entity is responsible. Cable TV and broadband customers represent the largest potential network, at about 80 million subscribers [34]. About one-third of these customers are served by a single national provider (Comcast). We estimate that the population of Internet-connected thermostats exceeds six million. These devices are offered by several providers, some of whom already serve more than a million households. Automated teller machines are connected through private networks and the Internet but are less frequently served by a central provider.

Neighborhoods of 100–300 homes served by residential cable TV systems are typically connected to neighborhood nodes. These nodes are especially attractive grid sensors because they have uninterruptible power supplies [35] and can therefore actively signal to the service provider when a loss of grid power occurs. In addition, the cable nodes can be associated with precise locations that are not subject to customer privacy constraints.

About 20,000 households participated in ecobee's DYD program in 2017 and more than 60,000 are participating in 2018. SCADA-equipped substations are listed for comparison [36]. This is typically the geospatial extent to which a utility has real-time visibility when smart meters are not configured to provide real-time data. These data may be fed into grid authorities but are not fed into a national entity.

Table 2. Populations of network-connected sensors

Network-connected Device/Sensor	Estimated Sensor Population (millions)
Cable TV boxes and Internet modems	~ 80
Internet-connected thermostats	~ 6
Bank automated teller machines (ATMs)	0.5
Cable TV and Internet network nodes	0.25
SCADA-equipped substations	0.07
Ecobee DYD thermostats (late 2018)	0.06

Table 2 shows that several existing sensor networks could provide equal or higher resolution and geospatial coverage of outages than substations equipped with SCADA devices. The DYD network has lower resolution than substations, but the number of participating thermostats will likely overtake substations in 2019. The DYD program illustrates how quickly a network of Internet-based sensors can be established and provide actionable information. The network can also be built relatively inexpensively where it can piggyback on an existing infrastructure. Ultimately, the network of cable TV nodes appears to be the most attractive because it offers high geospatial resolution and active sensing. The technical specifications of cable nodes are standardized so, in principle, an integrated national outage monitoring system could be created by linking output from the major cable providers.

The most obvious users of this information are entities responsible for grid security and resiliency, utilities, emergency management authorities, and insurance companies; however, there may be other commercial applications of high-resolution outage data. For example, a service provider could generate an “electricity reliability score” at the neighborhood level, similar to the “walkability score” now available for some neighborhoods [37]. This information could affect housing purchases because persons relying on medical equipment or using sensitive electrical equipment would consider either avoiding these areas (or investing in back-up generation). A service provider could also publish reliability scores for cities or whole utility service areas.

6.4 Future Work

Future research might advance in at least three directions. First, the viability of the method needs to be demonstrated in real time. A utility could partner with a provider of Internet-connected devices to obtain real-time outage detection services. Does this network of sensors provide additional visibility into outages and provide value beyond existing outage management systems? Smaller studies might also permit detailed verification (and improvement) of the algorithms used to distinguish between network outages (and other reasons for the thermostat not communicating) and power failures.

By 2021, this network of DYD thermostats will exceed the number and geospatial coverage of all utility-managed SCADA systems in the United States. Further research is needed to determine if the DYD data—or an alternative network—can complement conventional utility data gathering methods as means of uniformly tracking long-term improvements in grid reliability.

Finally, Internet-connected devices could serve as even better grid sensors. For example, the nodes in cable TV networks appear especially attractive. Their capabilities deserve additional investigation and testing.

7. Conclusions

A new method for detecting power outages was introduced. The method relies on frequent communications between Internet-connected devices in homes—in this case, thermostats—and service providers. A power outage severs the communication link to these devices, which is quickly noticed by the providers—sometimes in fewer than five minutes.

This work demonstrated that a network of Internet-connected thermostats could serve as power outage sensors. The approach was applied to nine major outage events, including hurricanes and windstorms. For Hurricane Irma, thermostat-based outage maps and impacts were compared to detailed utility data. The network of about 1,000 thermostats provided quantitatively similar results with respect to the number of homes without power (and then reconnected) and most severely affected regions.

The DYD data captured roughly 82 percent of the outage-hours reported by utilities for major events in 2017. With further improvements in data processing, connected thermostats—or other connected devices—could be an accurate means of estimating outage-hours from major outage events and tracking these events at a national scale in a uniform manner.

Detection of ordinary outage events at a national scale is not yet feasible with current techniques. The DYD data still contain too much noise to observe power outages that occur in small regions and at very low frequencies. Future improvements in algorithms should be able to better distinguish actual power outages from other reasons that the connected devices are not transmitting data, but the noise can never be completely eliminated.

This method generated regionally uniform outage data that would give emergency authorities better visibility into the scope and magnitude of outages. This information is not sufficient for utilities to manage their system—SCADA data and other sources are still essential—but it could help them prioritize aid to the most severely affected communities. A separate monitoring system may also give a utility visibility into grid status when the conventional SCADA data are compromised through cyber disruption.

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